Helsinki Center of Economic Research

Discussion Papers

Type of Education and the Gender Wage Gap

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Discussion Paper No. 128
October 2006

ISSN 1795-0562

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HECER
Discussion Paper No. 128

Type of Education and the Gender Wage Gap*

Abstract

This paper investigates the role of university majors in explaining the gender wage gap. Using data from the Confederation of Finnish Industries, significant gender differences in majors among white-collars are found. These differences in education account for 36.8 % of the gender wage gap among young white-collars with a bachelor level degree after controlling for age, year, gender, region, industry and firm size. The corresponding number for young white-collars with a master level degree is 30.4 %. There are no considerable differences in the effects of majors between new entrants and white-collars having more work experience. Furthermore, similarity of results between OLS and fixed effects estimations implies that the effect of university majors is unlikely to reflect unobserved heterogeneity. Finally, women's gains from equalizing educational distributions do not depend in significant way on the price structures used. In conclusion, the findings in this paper strongly support the idea that steering women toward male-dominated majors would significantly reduce the observed gender inequality in wages.

JEL Classification: J16, J31, J71

Keywords: gender wage gap, type of education

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* I thank Alan Manning, Pekka Ilmakunnas, Rita Asplund and Antti Kauhanen for valuable comments. The usual disclaimer applies. I thank the Academy of Finland, FDPE, the Helsinki School of Economics, and the Yrjö Jahnsson Foundation for financial support. I am also grateful to the Confederation of Finnish Industries for giving allowance to use the data.

1. Introduction

A large amount of research has evolved exploring the question of why a substantial gender wage gap exists in practically all labor markets (see Altonji and Blank 1999; Blau and Kahn 2000; Kunze 2000, for a review). In terms of the methodological approach applied, studies in this line of research have commonly followed the example set by Blinder (1973) and Oaxaca (1973). Blinder and Oaxaca suggest a decomposition in which the gender wage gap is decomposed into one part explained by sex differences in qualifications and another part due to gender differences in the estimated rewards on those qualifications.[1] Studies differ with respect to the explanatory variables included in the wage equations, but despite using a wide variety of variables (e.g. work experience, job tenure, years of education, field of industry, occupation and so on), a sizeable unexplained gender wage gap typically remains. Some researchers interpret this as evidence of labor market discrimination towards women whereas other argue that the unexplained part of the wage gap results from researchers' inability to control for all the relevant productivity-related characteristics of workers.

One potentially important determinant of wages, which has nevertheless received rather little attention so far, is, somewhat surprisingly, education. Even though almost all studies of the gender wage gap include some measure of the *quantity* of education in the wage regressions, the *type* of schooling is typically controlled for only at a very general level. As is pointed out in Machin and Puhani (2003), this lack of attention to the type of education is probably partly due to the fact that many standard data sets like the Current Population Survey, the Panel Survey of Income Dynamics, and the British Household Panel Study do not contain detailed information on education.

There are, however, a number of reasons to believe that type of education is of considerable importance when it comes to explaining the gender-based wage gap. First of all, there are significant differences in wages between fields of education. For example, workers with a degree in technology have on average higher incomes than those who have completed a degree in humanities and arts. Secondly, it is well known that men

[1] There are many other decomposition methods, like those suggested by Juhn, Murphy and Pierce (1993) and Brown, Moon and Zoloth (1980), but the Blinder-Oaxaca decomposition is by far the most often applied method in the gender wage gap literature.

and women differ with respect to their educational choices. Men are typically more heavily concentrated on technical education whereas women are 'overrepresented' in subjects like social sciences, education, and humanities and arts.

All the existing studies of the importance of the type of education in explaining the gender wage gap emphasize that the type of schooling matters.[2] The exact contribution of the type of education varies between 10 to 30 percent of the overall gender wage gap depending among other things on the measure of education applied. There are, however, some important issues that have been explored only little, or not at all, so far, and to which this paper tries to contribute. First of all, all the earlier studies in this particular line of research base their conclusions on parameter estimates drawn from the OLS wage regressions. However, it may be the case that differences in education arise from differences in unobserved individual characteristics like preferences and abilities, and that these characteristics may contribute to higher wages as well. If this is true, then policies aiming at reducing the gender wage gap by steering women toward male-dominated majors will have only small effects. Studies applying OLS estimates have little to say about the role played by unobserved individual heterogeneity. I, on the other hand, have panel data enabling me to compare OLS and fixed effects estimation results and to examine, at least to some extent, whether time-constant unobserved heterogeneity accounts for the effects of majors on the gender wage gap.

Secondly, there is a lack of research investigating how the importance of the type of education as a determinant of wages differs by the stage of a working career. It is reasonable to assume that at the time of labor market entry when workers are still quite similar in terms of other individual background characteristics than education, the contribution of the type of education to the gender wage gap is likely to be particularly large. However, some question remains as to whether the type of education plays such an important role also among workers having more work experience. Many of the earlier studies focus exclusively on the early career and to my knowledge, only Gerhart (1990) has made comparative analysis between new entrants to the labor market and more

[2] The existing literature on the role played by the type of education in explaining gender-based wage differentials is thin. One might quote Daymont and Andrisani (1984), Gerhart (1990), Brown and Corcoran (1997), Weinberger (1998), Machin and Puhani (2003), Black et al. (2004), and Liu (2006) as a fairly complete list of the studies on this particular topic.

experienced workers. Gerhart (1990) observes using data from a particular U.S. firm that college major plays a key role in explaining the gender gap in starting wages but college major is, however, much less important in explaining the wage gap between more experienced men and women. I also investigate new entrants to the labor market separately from more experienced workers to explore how the importance of the type of education in accounting for the gender-based wage gap differs by the stage of a career.

Third, many of the earlier studies have been forced to settle for a fairly broad measure of education. This leaves open the question of how much these broad educational categories hide information that is valuable in explaining the gender wage gap. My data, however, have exceptionally detailed information on education: there are up to 247 majors represented in the data (although 'only' 241 of those are used in the regressions). Furthermore, my data set is also considerably larger compared to many of the earlier studies.[3] This enables me to get reasonable precise estimates of the effects of majors despite the use of detailed education variables.

Fourth, with the exception of Machin and Puhani (2003), all the other earlier studies focus exclusively on the U.S. labor market. However, there are many significant differences in labor market institutions between the U.S. and those of the continental European countries.[4] These differences in institutional arrangements may not only explain the variation in the size of the overall gender wage gap between the U.S. and Europe (Blau and Kahn 1996) but they may also have effects on the relative importance of different individual background characteristics with respect to the gender-based wage

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[3] To illustrate this, I present the number of observations and educational categories used in some of the previous papers. Daymont and Andrisani (1984) used 2 800 observations and ten different college majors. Brown and Corcoran (1997) have up to 20 different majors and 17 000 observations. (They also use another data set but it is smaller both in terms of education groups and observations). Examples of studies that use fairly detailed measures of education are Gerhart (1990), Machin and Puhani (2003), and Weinberger (1998). Gerhart has information on 65 college majors and the data used by Machin and Puhani report up to 124 different subject areas. Weinberger reports as many as 246 college majors. But in these three papers the number of observations is quite small. Gerhart estimate his model by using 4 600 observations, Machin and Puhani have 5 000 observations in their smaller data, and finally, Weinberger makes her analysis using information on about 6 000 workers. I have over 200 000 observations of workers with a bachelor level degree and about 160 000 observations of workers who have completed a master level degree. In the case of bachelor level, there are 247 majors represented in my data. The corresponding figure for the master level is 176. See Table 2A for more detailed information about the number of education groups and number of observations.

[4] One example of these differences is unionization. In many continental European countries, most notably in the Scandinavian countries, labor markets are highly unionized with comprehensive collective wage agreements.

differentials (Albrecht et al. 2003). Therefore, to improve our understanding concerning the mechanisms (of which the type of education forms one part) behind the gender wage gap, it may be useful to do research in different institutional setups. In this respect there is a gap in the existing literature. This paper contributes to the filling of the gap by examining the role of the type of education in explaining the gender wage differentials in the Finnish labor market.

Finally, the data used in most of the existing studies dates back to the 1980s. Taking into account the considerable changes in the educational distributions during the past 15 years, most notably the significant increase in the fraction of workers with college or higher education, research applying data from more recent years are needed. My data set reaches up to 2004 providing thus fresh evidence of the effects of education on the gender-based wage gap.

In this paper, I examine the importance of the type of education in accounting for the gender gap in wages among white-collar workers with a university degree. The data set comes from the records of the Confederation of Finnish Industries (EK) and it covers the period 1998-2004. The overall degree of unionization is very high in the Finnish labor market, and EK is the largest organization on the employers' side. The EK data are very suitable for the analysis in question. First of all, they contain exceptionally detailed information on education. Secondly, the size of the data is also large enabling me fully to utilize the detailed measures of education. Thirdly, it cannot be stressed enough that the EK data are of very high quality since the information comes from the employers' registers. As a result, there is virtually no response bias and all information in the data is highly reliable. This is a clear advantage over the typically used surveys directed to employees. Finally, the panel structure of the EK data makes it possible to explore the question of whether the effects of university majors to the gender wage gap reflect unobserved heterogeneity.

As a drawback it must be mentioned that the EK data set is not a representative sample of the whole Finnish economy. In the EK data, women are underrepresented and the gender wage gap is somewhat larger than what is the case in the Finnish labor market in general. I nevertheless apply the EK data in order to make use of the unusually detailed measures of education. The problem related to whether to use large representative data sets or more specific data sources is common for all researchers doing empirical analysis. The advantages of the representative data sets are obvious. But the problem with those data sets is that they often lack detailed information on relevant human capital variables. Therefore, researchers are sometimes forced to turn to more specialized data sets, even at the risk of losing some of the generability of their results. At this point, it should, however, be emphasized that my results are not without significance due to the use of somewhat more specialized data. First of all, the EK data set covers the Finnish manufacturing sector. The employment share of manufacturing was 20 % and its share of the total production was around 25 % during the period of investigation. The sector under study is thus an important part of the Finnish economy. Furthermore, as discussed in Korkeamäki and Kyyrä (2006), the EK data are rather similar in terms of many key characteristics to the other Nordic data sets on white-collar workers in the manufacturing sector. Therefore, the conclusions drawn in this study are not only of interest when the Finnish manufacturing sector or the Finnish labor market in general are considered, but also on a larger scale.

To give a preview of some of the main findings of the paper: the type of education explains a considerable amount of the gender gap in wages among university graduates in the Finnish manufacturing sector. Even when a broad measure (i.e. eight different categories) is applied, the type of education accounts for as much as 25 percent of the gender wage gap among the new entrants to the labor market after controlling for age, year, gender, region, industry and firm size. The corresponding figure for workers having more work experience is smaller, about 13 percent. I find, however, that the broad major categories hide much valuable information. Controlling for the same set of background variables while adding detail on education raises the contribution of majors to the gender wage gap by over 10 percentage points for both the new entrants and more experienced workers. The effects of majors differ somewhat depending on whether a worker has completed a bachelor or master level degree, but irrespective of the level of degree or the stage of a career, the contribution of majors to the gender-based wage gap is remarkable large for a single factor. I also find little difference between OLS and fixed effects results suggesting that unobserved heterogeneity is unlikely to account for the effects of university majors. Furthermore, my conclusions do not seem to be sensitive to the reference wage structure used. These results thus strongly support the idea that policies aiming at reducing gender inequality in wages should also consider factors influencing educational choices.

The rest of the paper is organized as follows. In the next section, I present the data and illustrate gender differences in the type of education among highly educated white-collar workers. Section 2 also explores wage differences between the fields of education. Section 3 starts with a discussion about the methodology used in the paper. Then I continue to show the basic results separately for the new entrants to the labor market and for workers having more work experience. I also examine the importance of unobserved factors with respect to the conclusions drawn from the basic analyses. Section 4 explores the question of how much women's wage changes caused by equalizing educational distributions between genders depend on the wage structure used. Section 5 gives a summary of the paper and reports the main conclusions.

2. The Data and some Descriptive Statistics

2.1 The EK Data

The data used in the paper come from the records of the Confederation of Finnish Industries (EK). The Finnish labor market is highly unionized with comprehensive collective wage agreements and EK is the main organization of employers. There are member firms from construction, transportation, services, forest and energy industry, but the most important sector represented in the data is manufacturing. The firms that are affiliated with EK account for over two thirds of the value added of the Finnish manufacturing sector and a clear majority of the workers in manufacturing are employed in the member firms of EK.

The information in the EK data is gathered by sending surveys directed to the employers. Since the information comes directly from the administrative records of the member firms, the reliability of the EK data can be considered as exceptionally high. Also because it is compulsory for the member firms to provide the required information, the non-response bias is practically non-existent in the data.

EK gathers information on both white-collar and blue-collar workers, but in this paper I restrict myself exclusively to white-collar workers. Furthermore, only full-time workers (i.e. individuals who work at least 35 hours per week) aged between 17 and 65 are included in the analysis. I focus on university graduates because it is at this level of education where the information on the type of schooling is most detailed.[5] The resulting data cover the period 1998-2004 and contain over 360 000 observations. Summary statistics are shown in Table 1A. More about the advantages and drawbacks of the EK data are discussed in the introduction of this paper.

2.2 Gender Differences in University Majors

In this section, I describe gender differences in university majors among white-collar workers. Figure 1 shows the distributions of fields of degrees by gender. For illustrative purposes, I use broad measures of education. As can be seen, white-collar men and women differ widely in their educational choices. Men are heavily represented in technology whereas over 40 percent of women have obtained a degree in social sciences and business. White-collar women have also degrees in humanities and arts more often than their male colleagues.

When the distributions reported in Figure 1 are compared to the corresponding distributions among university graduates in the Finnish labor market in general, the most notable difference is that workers with a degree in technology are clearly overrepresented in my data. This holds for both men and women. However, women's tendency to choose fields like social sciences and business or humanities and arts more often than men is a characteristic of the Finnish labor market in general, not just a feature of the EK data. Furthermore, the degree of gender segregation by fields of education does not seem to be particularly high in the EK data compared to the Finnish labor market as a whole. To illustrate this, I use another data source which comes from Statistics Finland and which is a representative sample of the Finnish labor force. Also this data contain information on the *broader* fields of education and the classification of fields is comparable between the two data sets. Using these data sources I compute the Duncan and Duncan segregation

[5] University degree in my data correspond to 5A-programmes in ISCED 1997-classification.

index for workers with a university degree in 2001.[6] The results are rather similar for both data sets: the value of the index is 0.53 for the EK data and 0.45 for the sample from Statistics Finland.

Table 1 examines gender differences in education within the broader fields of education. The purpose of Table 1 is to investigate whether the choices of majors differ between men and women who have obtained a degree in the same field of education. Again, this issue is explored by calculating the Duncan and Duncan segregation index. According to the results reported in Table 1, men's and women's educational choices differ even within the same field of education.

2.3 Wages and University Major

It is well-known that there are wage differentials by field of education. For example, graduates in humanities typically earn less than workers with a degree in technology. Figure 2 illustrates this for my data. As can be seen, for both bachelor and master level graduates (BA and MA level respectively), fields like technology or business are associated with high incomes whereas workers who have specialized in humanities and arts must settle for lower incomes. These general conclusions hold for both genders, as can be noticed from Figure 3.

There is considerable wage variation also within the fields of education. To illustrate this, I have calculated wage profiles for three common majors in technology shown in Figure 4. As can be seen, graduates in computer sciences earn considerably more than graduates in mechanical engineering or in construction engineering. Similar kinds of wage differentials by major can be observed also in other fields of education. Furthermore, these wage differentials remain even after I control for gender, so the observed wage differentials by major are not driven by differences in the proportion of women and men graduating in the majors in question.

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[6] The Duncan & Duncan segregation index is defined as $S = 0.5\sum_i m_i - f_i$ where m_i denotes the share of the male labor force in education field i, and f_i is similarly defined for women. The Duncan & Duncan index takes values between 0 and 1 indicating the proportion of men (women) that would have to be redistributed across fields of education in order to reach equal educational distributions between genders.

It is these kinds of gender differences in educational choices and wage differentials between university majors that inspire me to investigate the role of sex-based differences in education in explaining the wage gap between men and women.

3. University Major and the Gender Wage Gap

3.1 Methodological Framework

The contribution of any productivity related characteristics X to the gender wage gap can be calculated as $(\overline{X}_m - \overline{X}_f)\hat{\beta}$ where $\overline{X}$ is the average of X, $\hat{\beta}$ denotes the estimated coefficient(s), and m and f refer to male and female workers respectively. One of the key decisions that a researcher must make concerns the sample from which $\hat{\beta}$ is estimated. There are various possibilities: one may estimate coefficients using male-only or female-only samples, or alternatively, some weighted average of male and female samples. Among researchers, there is plenty of debate about which reference wage structure one should prefer (e.g. Reimers 1983; Cotton 1988; Neumark 1988; Gupta et al. 2003). In my case, however, there is one practical issue which strongly supports the use of the pooled sample (i.e. pooling men and women together). Because of the significant gender differences in educational choices, there are majors represented in the data in which there are only few men (women) but plenty of women (men). If wage equations are estimated separately for men and women, the standard errors for sex-atypical majors are typically high. Furthermore, these imprecisely estimated coefficients would then be multiplied by large differences in the X's. To avoid this, I estimate wage equations using the pooled sample. I do realize, however, that the results may be sensitive to the choice of reference wage structure and therefore in Section 4, I investigate to what extent the possible wage gains experienced by women from equalizing major distributions depend on whether male or female prices are used.

I estimate three different wage regressions. Specification I is an augmented Mincerian wage equation including only age, age squared, and dummies for region, year and gender. In Specification II, industry and firm size dummies are added to the wage model. Finally, Specification III also includes occupation. Since university major undoubtedly affects occupational determination, Specification III is likely to produce an underestimate of the ‘true’ wage effects of majors. It is, however, of some interest to compare the results of Specification III to the other specifications as it sheds light on the mechanisms through which the type of education affects wages. In all wage regressions, log of hourly wage is the dependent variable. There is no direct information on hourly wages in the data, but they can be calculated using information on monthly wages and weekly working hours. Wages are converted into 2004 money using the cost-of-living index of Statistics Finland.

For each of the three wage specifications, I estimate two different versions. One, that contains only broad measures of education (i.e. 8 different categories), and one, that enters detailed controls for university majors (up to 241 different majors). The idea behind this is to investigate whether broad measures of education hide information that might be useful for explaining the gender wage gap.

I experimented with several different wage models. First of all, I examined whether the relationship between wage and age is well-approximated by a quadratic functional form by including even higher terms of age in the wage equation. It turned out that the quadratic specification seems sufficient to capture the variation in wages. I also allowed the effects of industry and firm size to vary with the worker’s age by including interaction terms in the wage model. The interaction terms proved to be mostly insignificant at the usual significance levels, and more importantly, they seemed to be of no importance with respect to the conclusions presented in the paper. Therefore, I exclude them from the analysis that follows. Finally, I investigated interactions between age and university majors. This was motivated by the often presented hypothesis according to which women’s educational choices differ from those of men because women experience more career interruptions than men. As a result, women’s incentives to choose majors that prepare them for jobs that require considerable investments in job-related training are reduced. If this is the case and if there are differences in wage-experience profiles between jobs with different degree of investment intensity, then perhaps a more appropriate way of modeling the impact of majors on wages is through using interactions between age and majors together with major dummies. Although I cannot reject the hypothesis concerning the joint significance of the interaction terms, I decided not to include them in the wage regressions but use the approach applied in the earlier research instead, and enter educational variables into the wage model only through dummy variables.[7] The main reason for this is that in order to reach identification for the interaction terms, I need to restrict the number of major categories rather considerably. The lack of identification with a detailed set of majors is partly due to the fact that there are many age-major cells with no or only a few observations. Furthermore, the differences in the wage *profiles* between majors are actually quite small which naturally makes it hard to get estimates for the interaction terms.[8] The rather small differences in the wage profiles between majors appear already from a quick inspection of Figures 2 and 3. Also the mean comparison tests concerning the average yearly wage growth by field of education confirm this.[9] Therefore, the possible problems due to misspecification of the wage model resulting from using only major dummies and excluding the interaction terms are likely to be small.

3.2 Results for the New Entrants to the Labor Market

The contribution of university majors to the gender wage gap is likely to be strongest at the time of labor market entry when workers are still quite similar in terms of other individual background characteristics than education. Therefore, I start my analysis by examining new entrants to the labor market. I define 'new entrant' as a worker who has at most one year of (potential) experience when first observed in the data and who has completed a university degree at age 30 or younger. This results in 26269 male and 9966 female observations at the BA-level and 19649 male and 9759 female observations at the MA-level. By distinguishing new entrants from other workers I also facilitate comparison between my results and those of the earlier literature as many of the previous studies concentrate exclusively on workers at their early careers.

[7] Section 3.4, where I estimate a fixed effects model, forms an exception to this.
[8] The finding that differences in the wage profiles between majors are quite small is in some sense in line with the Mincer's (1974) famous observation that the wage-experience profiles are similar for different educational levels.
[9] I executed the mean comparison tests for broad major categories using both average yearly wage growth calculated across the whole career (from age 24 to 60) and also across different stages of a career (age groups analyzed were 24-30, 31-40, and 41-50).

Before I turn to the decomposition analysis, I discuss briefly the OLS regression results. Because of lack of space, I do not present the regression tables, but they are available from the author upon request. Basically, the results are what one could expect (based on economic theory and earlier empirical studies). For example, wages increase with age but at a decreasing rate. There are also some wage differences between industries, and larger firms seem to pay higher wages than smaller firms which, again, is in line with earlier studies (e.g. Brown and Medoff 1989; Winter-Ebmer and Zweimuller 1999).

Table 2 shows the decomposition results for new entrants with less detailed controls for education. The first row presents the gender gap in log hourly wages. As can be seen, there exists significant gender wage gap already on entry to the labor market: female entrants with a BA-level degree lag behind male entrants in average wages by 14 log points whereas the gender gap in average wages for entrants who have completed a MA-level degree is 10.3 log points. Row 2 shows that 22.8 % of the gender wage gap among entrants with a BA-level degree can be explained by differences in university major alone, controlling for age, year, region and gender. The corresponding figure for the MA-level entrants is 16.4 %. Adding controls for industry and firm size makes only little difference in terms of the contribution of field of education to the gender wage differentials. As was expected, controlling for occupation decreases the size of the gender wage gap explained by education, but the type of education seems to matter even within occupations: in the case of BA workers the contribution of education amounts to 10.9 % of the gender wage gap after controlling for occupation and the corresponding figure for MA workers is somewhat higher, 12.8 %.

Table 3 is similar to Table 2 but instead of controlling for broad educational categories, Table 3 presents the decomposition results with a detailed measure of education. As can be seen, there are considerable gains to be achieved in terms of the proportion of the gender wage gap explained by using a more detailed measure of education. Considering Specification I, an additional 16.2 percentage points of the early career gender wage gap can be explained by detailed measures of education in the case of entrants with a BA-level degree. The corresponding figure for the other graduate group is 18.4 percentage points. These figures imply that after controlling for basic variables the proportion of the gender wage gap due to education amounts to 39 % and 34.8 % among entrants with a BA-level and MA-level degree, respectively. This is a remarkably large contribution for a single factor. As before, also here employer characteristics (size and field of industry) have a relatively small impact on the results. Even after including controls for occupation the contribution of university majors to the gender wage gap is still huge, 20.3 % and 26.9 % of the gender wage differentials among BA-level and MA-level graduates respectively.

My results thus suggest that university majors matter in accounting for the wage differentials among new entrants to the labor market. Furthermore, the estimated effects of type of education to the gender wage gap roughly correspond to the results presented in earlier studies. For example, Daymont and Andrisani (1984) and Gerhart (1990) using data from the U.S. labor market conclude that college majors account for 20 to 40 percent (depending on specification) of the early career gender wage gap. This similarity between my results and those for the U.S. is itself of some interest taking into account the clear differences in the institutional setups between Finland and the United States.

As a robustness check, I made a similar analysis by restricting the size of education and occupation 'cells' to at least 30 observations. The purpose of this exercise was to make sure that imprecisely estimated coefficients due to small numbers of observations in some education and occupation categories do not drive my conclusions in any way. The decomposition results drawn from regressions using this restricted sample were practically identical to those discussed above.

3.3 Results for Experienced Workers

The previous section showed that the university major is an important factor behind the gender wage gap among new entrants to the labor market. In this section, using the total EK data excluding workers considered in Section 3.2, I investigate whether university majors play such a key role also among more experienced workers.

The OLS regression results for this sample are not very different from those for new entrants. Also here I find wage differentials between industries and wage gains from being employed at a larger firm. Furthermore, the coefficients for education and occupation are mostly statistically significant at the conventional significance levels.

Table 4 presents the decomposition results for the total data excluding entrants using a less detailed classification of education. As can be seen from the first row of the table, the gender gap in average log wages is considerably higher among more experienced university graduates compared to the new entrants to the labor market, especially for MA workers (0.14 vs. 0.18 among BA workers and 0.10 vs. 0.20 among MA workers). This difference in the gender wage gap between entrants and more experienced workers is undoubtedly partly due to cohort effects but several studies have shown that the gender wage differentials tend to grow with work experience (e.g. Loprest 1992; Manning and Swaffield 2005; Napari 2006). As could be expected, the university major accounts typically for a smaller proportion of the overall gender wage gap among experienced workers compared to the new entrants but the differences in this respect are surprisingly small, at least when MA workers are considered. The point made earlier in the case of new entrants, namely that controlling for university majors even at a rather broad level of detail goes a good way in understanding the gender wage differentials, holds also here. For example when Specification II is considered, about 14 % of the gender differential in wages among both university groups can be attributed to gender-based differences in majors, as is reported in Table 4.[10]

In Section 3.2 I illustrated that broad university major categories may hide information that is valuable in explaining the gender wage gap. This is the case also when more experienced workers are analyzed, as can be seen by comparing Table 5, which reports the decomposition results for a model with detailed measures of education, to Table 4. Adding detail on university majors raises the contribution of majors to the gender wage gap among workers with a BA-level degree from 8.9, 13.4, and 7.2 percent of the gap to 30.3, 31.8, and 20.0 percent in the case of Specification I, II, and III, respectively. The gains from using more detailed measures of education are smaller among workers with a MA-level degree but also among them the proportion of the gender wage gap attributable to university majors increases significantly as a result of the

[10] In Specification II, the negative value for the contribution of other characteristics to the gender wage gap among workers with a BA-level degree is due to the fact that (BA) women are more heavily concentrated in high-paid industries compared to (BA) men.

improved measure of education. These numbers are somewhat higher than what for example Machin and Puhani (2003) found using data for the UK and Germany. After controlling for age, region, part-time work and sector of employment, they found that gender differences in university majors explain 18.7 % of the overall gender differentials in wages in the UK and 8.6 % in Germany. One obvious reason for why I find larger effects of majors is that I control for more detailed major categories. And as was the case for the new entrants to the labor market, also for more experienced workers my results roughly correspond to the earlier research results for the U.S.

Again, my conclusions do not seem to be driven by small education and occupation 'cells' as the results are practically unchanged when I set restrictions to the minimum number of observations in education and occupation categories. Moreover, since I have presented evidence that the sex-based differences in the university majors are important in explaining the gender gap in wages not only among new entrants to the labor market but also among more experienced workers, the rest of the paper does not make any difference between the entrants and other workers.

3.4 Does Unobserved Heterogeneity Account for the Effects of University Majors?

The results reported in Sections 3.2 and 3.3 seem to suggest that encouraging women to choose more male-dominated type of education is one noteworthy policy option when trying to reduce the observed wage differentials between men and women. However, when the effectiveness of this policy option is considered, one crucial issue concerns to what extent the wage differences between different types of education are due to the fact that some types of education may offer more valuable human capital than others, and to what extent the wage differences arise from differences in individuals' unobserved characteristics. It may well be the case that some unobserved factors like preferences and abilities contribute to the gender differences in education and that these same factors, not the type of education itself, affect also wages. If this is true, then encouraging women towards male-dominated fields of education will have little impact on promoting gender equality in wages.

I analyze the possible role of unobserved heterogeneity for my conclusions by comparing the decomposition results drawn from OLS and fixed effects (FE) estimations. It is well-known that if unobserved heterogeneity causes correlation between the regressors and the error term then OLS produces biased estimates whereas the FE model yields still consistent results. Therefore, if the conclusions reported in the earlier sections are seriously biased by unobserved heterogeneity, I should observe the decomposition results based on OLS estimates to differ significantly from those based on the FE model. However, it should be noticed that even in the case OLS and FE models yield similar results I cannot completely rule out the possibility that my conclusions are biased by unobserved heterogeneity since the FE model accounts only for *time-invariant* unobserved factors. Any changes in workers' preferences or abilities over time would still cause biased results.

The wage functions estimated in this section are otherwise similar to those reported earlier in the paper and differ only in the way university majors enter the wage equations. Because the subject of degree is (mostly) time-invariant, in order to get coefficient estimates for majors in the FE framework, I use interactions between age and education variables.[11] Likewise, since gender is (in most cases) constant over time, it drops out from the wage model. I also need to decrease the number of different major and occupation categories rather heavily in order to reach identification.

Tables 6 and 7 report the results for workers with a BA- and MA-level degree respectively. Although I use a smaller set of major categories it should be mentioned that the interaction terms are rather imprecisely estimated due to lack of enough variability in the wage profiles between majors, an issue that was discussed earlier in Section 3.1. Therefore, one should perhaps avoid emphasizing too much the exact magnitudes of the contribution of university majors to the gender wage gap but concentrate on comparing OLS and FE results instead. By doing so, I can merely conclude that, for both graduate groups, the decomposition results are remarkably similar between the estimation methods, except for Specification III in which case university majors account for a much *larger* proportion of the gender wage gap when FE estimates

[11] Since I use interactions between age and education variables, what I actually estimate here is wage *profiles* by the type of education.

are used. The message emerging from Tables 6 and 7 is thus clear: on condition that unobservable heterogeneity can be sufficiently controlled for by applying the FE method, unobserved individual characteristics are not likely to account for the fact that the type of education matters a lot when it comes to explaining gender differentials in wages.

4. Gender Differences in Returns to University Majors

4.1 Measuring Gender Differences in Returns to Characteristics

Section 3 analyzed the contribution of university majors to the gender gap in wages by using parameter estimates from pooled-sample regressions. One might wonder whether my conclusions would have been different, had I used coefficients from male or female regressions as a reference wage structure instead. Many previous studies have found that men are better rewarded for investments in productivity-related characteristics like work experience and education, and that these return differences account for a substantial part of the gender wage gap (see e.g. Altonji and Blank 1999). This raises some questions about the effectiveness of promoting gender equality in wages by means of encouraging women to enter into male-dominated majors: if women earn lower returns to education than equivalent men, then any positive effects from equalizing educational distributions between genders are naturally reduced.

In the previous literature, the importance of gender differences in rewards for characteristics with respect to the gender wage gap has typically been evaluated by $\left(\hat{\beta}_M - \hat{\beta}_F\right)\overline{X}$ where $\hat{\beta}_M$ is a vector of parameter estimates for men, $\hat{\beta}_F$ is the corresponding term for women, and $\overline{X}$ refers to the sample mean (calculated from the male or the female sample, or from some weighted average of the two samples). Although this approach seems intuitive and is appealingly simple, it suffers from an identification problem which may cause serious problems for decomposition analysis.[12] As has been discussed for example in Jones (1983), Oaxaca and Ransom (1999), and Horrace and Oaxaca (2001), the coefficient effect depends on the choice of the reference category. And this

[12] Only in the case where the difference is calculated over all coefficients, including the intercept, the contribution of return differences to the wage gap is well-defined.

identification problem is not restricted to dummy variables only but applies also to affine transformations of continuous variables (Oaxaca and Ransom 1999).

One approach dealing with this problem is presented by Brown and Corcoran (1997). Following them, I define three new terms: $\Delta_M = (\bar{X}_M - \bar{X}_F)\hat{\beta}_M$, $\Delta_F = (\bar{X}_M - \bar{X}_F)\hat{\beta}_F$, and $\Delta = \Delta_M - \Delta_F$. As is discussed in Brown and Corcoran, Δ is invariant to how X is measured. Furthermore, Δ has a very intuitive interpretation. It tells us how much more (or less) women would gain from equalizing X if men's price structure is used instead of women's price structure. For example, if Δ gets a value of 0.1, women would experience a 10 percent higher wage change as a consequence of equalizing X if they faced male prices (instead of female prices).

I apply the method suggested by Brown and Corcoran to investigate possible gender differences in the returns to university majors. As can be seen from the definition of Δ, male-only or female-only majors inevitably contribute to Δ even though there cannot naturally exist gender differences in prices in these majors. Therefore, in the following I concentrate only on majors with both male and female observations. This reduces the number of majors 183 in the case of BA-level degrees and to 138 when workers with a MA-level degree are considered.

4.2 Gender Gap in Returns to University Majors

Table 8 reports the values of Δ for university majors. As can be seen from the table, there seems to be little evidence that women's gains from equalizing educational distributions would depend in any significant way on the price structure used. In Specification I, women with a BA-level degree would experience a 4.7 percent *higher* wage change from equalizing educational distributions if female coefficients are used instead of the male price structure. This effect is statistically significant at the 5 % level.[13] Adding controls for industry and firm size has negligible effects on the results. Including occupational dummies in the wage model reduces the value of Δ somewhat but Δ is still significantly negative among workers with a BA-level degree. For workers with a MA-level degree the

[13] The standard error for Δ is calculated as $\sigma(\Delta) = [\sigma^{\wedge 2}(\Delta_M) + \sigma^{\wedge 2}(\Delta_F)]^{0.5}$. I use heteroskedasticity- and autocorrelation-robust standard errors with clustering on the workers.

Δs are generally lower compared to the other graduate group: in Specifications I and II Δ equals roughly -0.01, and when controls for occupation are added to the model, Δ is not significantly different from zero. Hence, the results presented in Table 8 seem to suggest that my earlier conclusions concerning the importance of university majors in explaining the gender-based wage gap are not significantly driven by the choice of the reference wage structure. Furthermore, the figures in Table 8 appear to be reasonable in magnitude and roughly correspond to those reported in Brown and Corcoran (1997).

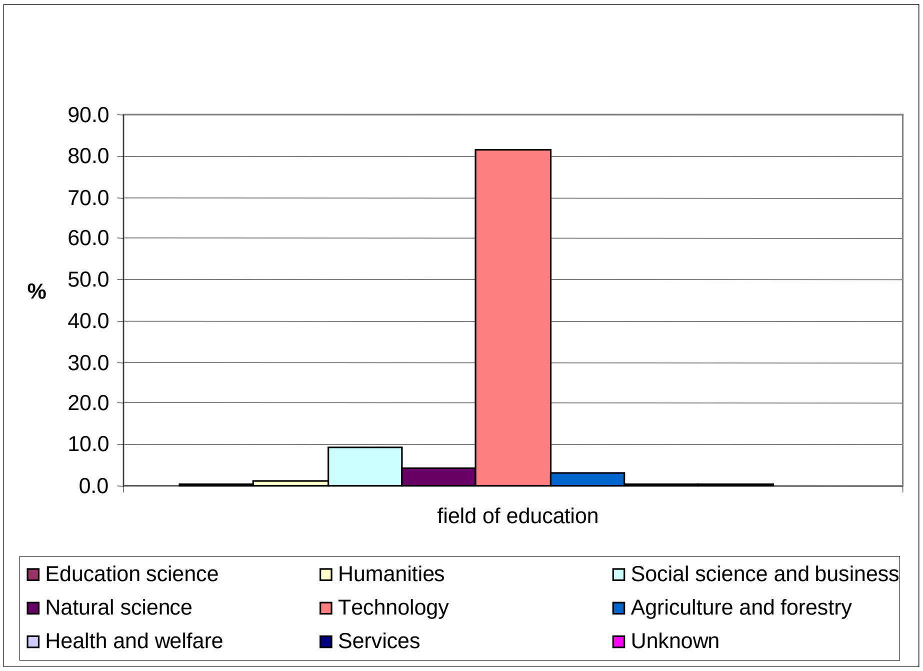
5. Conclusions

In this paper, I have focused on a single question: how important is the type of education in explaining gender differentials in wages among university graduates in the Finnish manufacturing sector. Using data for white-collar workers from the records of the Confederation of Finnish Industries, I find that the university major is a very important single factor behind the gender wage gap. When only eight major categories are used, gender differences in majors explain about 15 percent of the gender wage gap after controlling for age, year, gender, region, industry and firm size. Increasing the number of major categories up to 241, the contribution of majors to the gender wage gap raises over 30 percent, using the same set of other controls. There are some variation in the estimated size of the contribution of majors with the level of education (bachelor vs. master) and with the stage of a career (new entrants to the labor marker vs. more experienced workers), but irrespective of which of these worker groups are considered, the contribution of majors to the gender wage gap is remarkably large for a single factor.

I explore the possibility that unobserved factors explain at least some of the effects of university majors by comparing decomposition results based on OLS and fixed effects estimates. I find, however, little difference between the results of the two estimation methods suggesting that my conclusions concerning the importance of the type of education with respect to the gender wage gap are unlikely to be driven by unobserved heterogeneity. I also analyze the possible dependency of women's gains from equalizing educational distributions between genders on the price structure used. To do that, I apply the method presented by Brown and Corcoran (1997). I find no evidence that the change in wages experienced by women from steering them into male-dominated majors would depend in any considerable way on whether male or female prices are used. Hence, my results strongly support the idea that equalizing fields of education between genders would significantly reduce observed gender inequality in wages.

Figure 1: Distributions of fields of university degrees

Men:



Women:

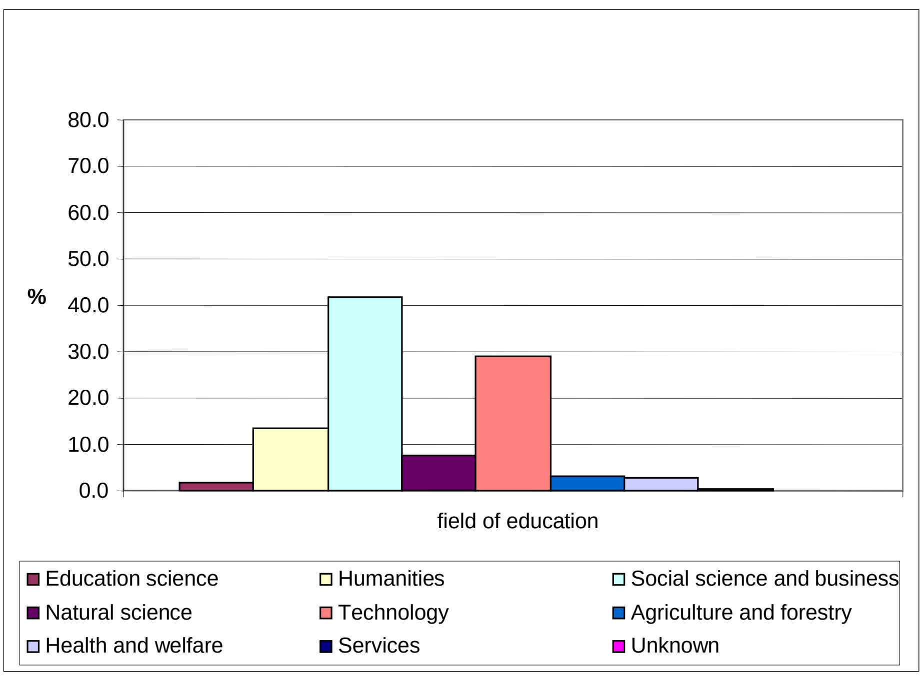
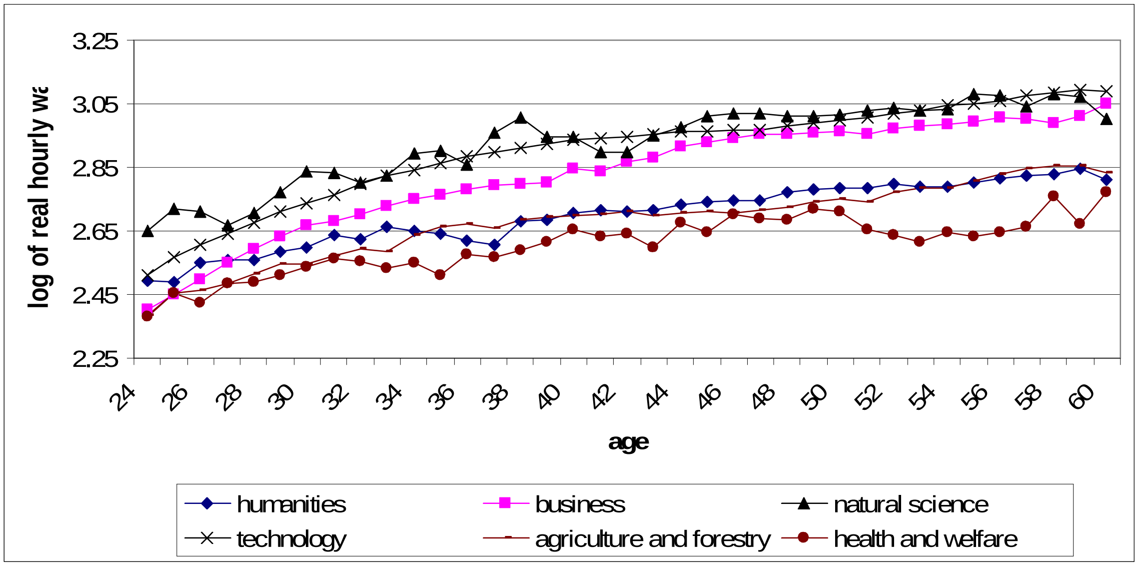
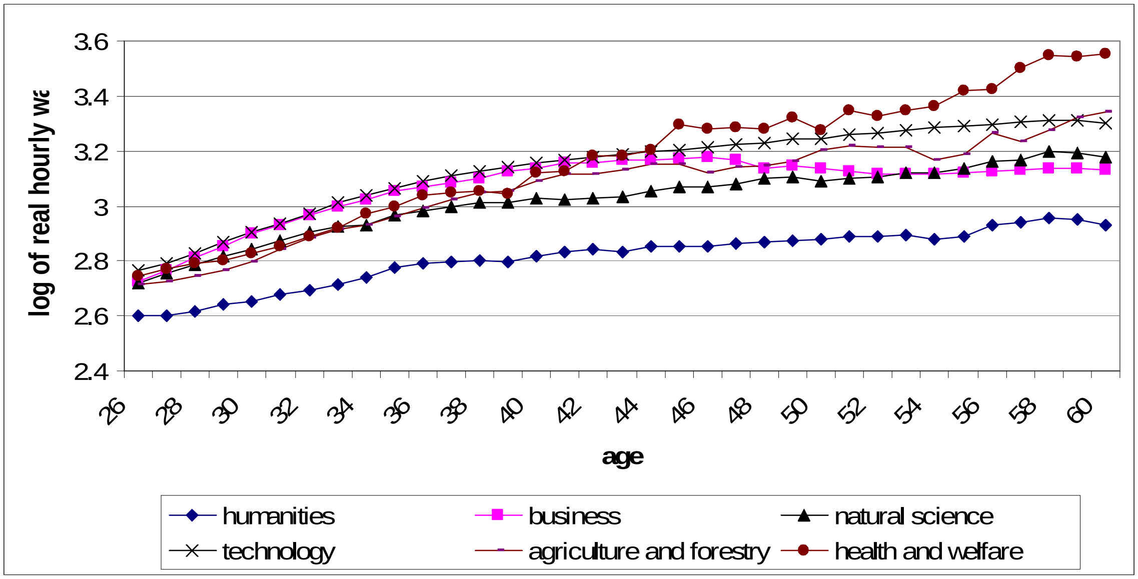


Figure 2: Wage differentials between fields of education

Bachelor level:



Master level:

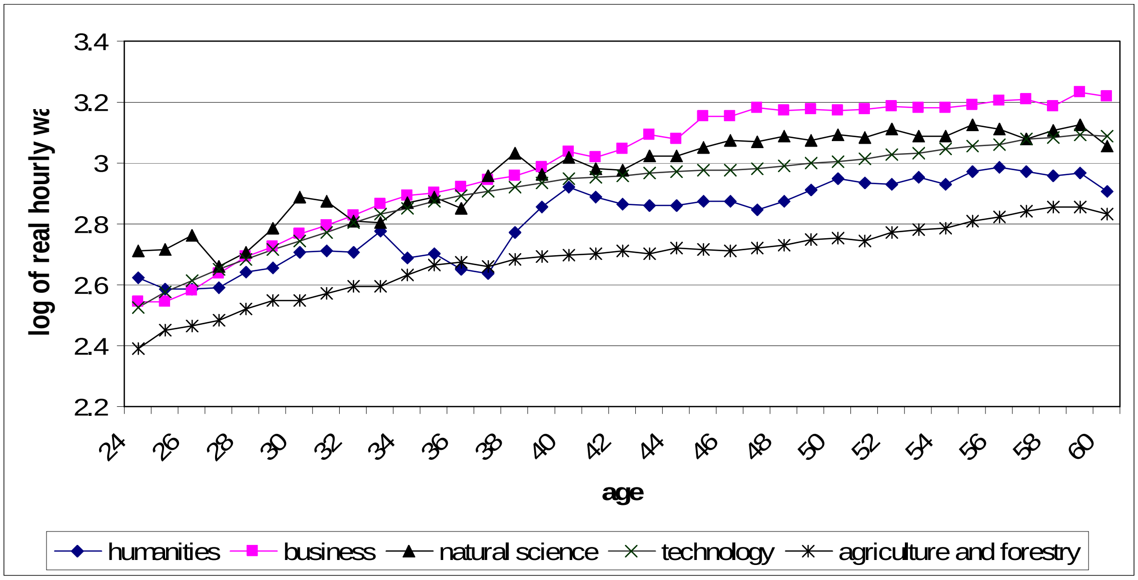


Notes:

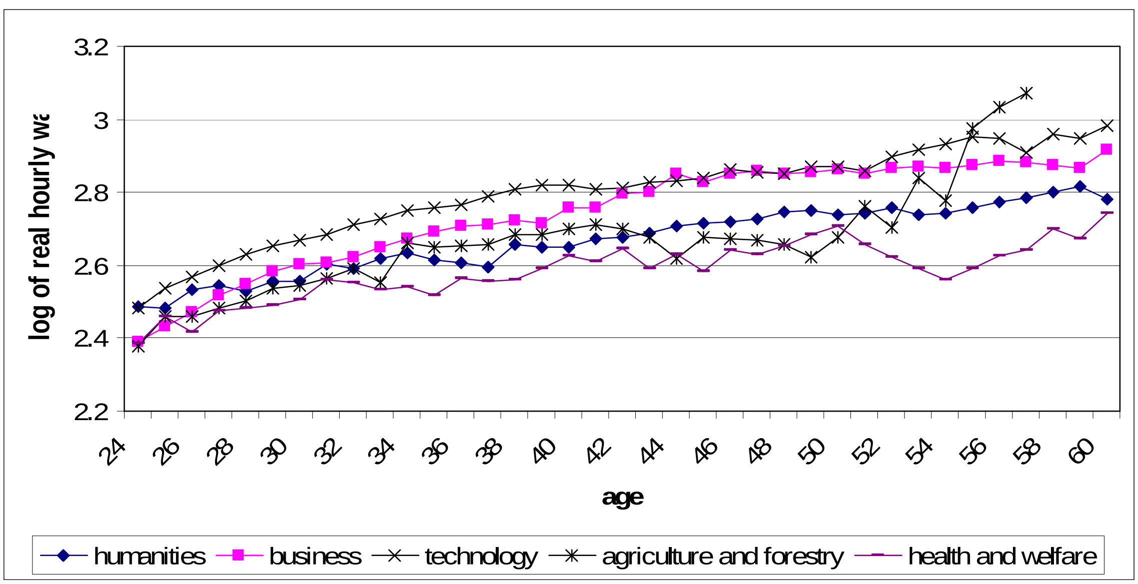
1. Education science and services are not included due to rather small number of observations in many age cells.

Figure 3: Wage differentials between fields of education by gender

Bachelor level: men

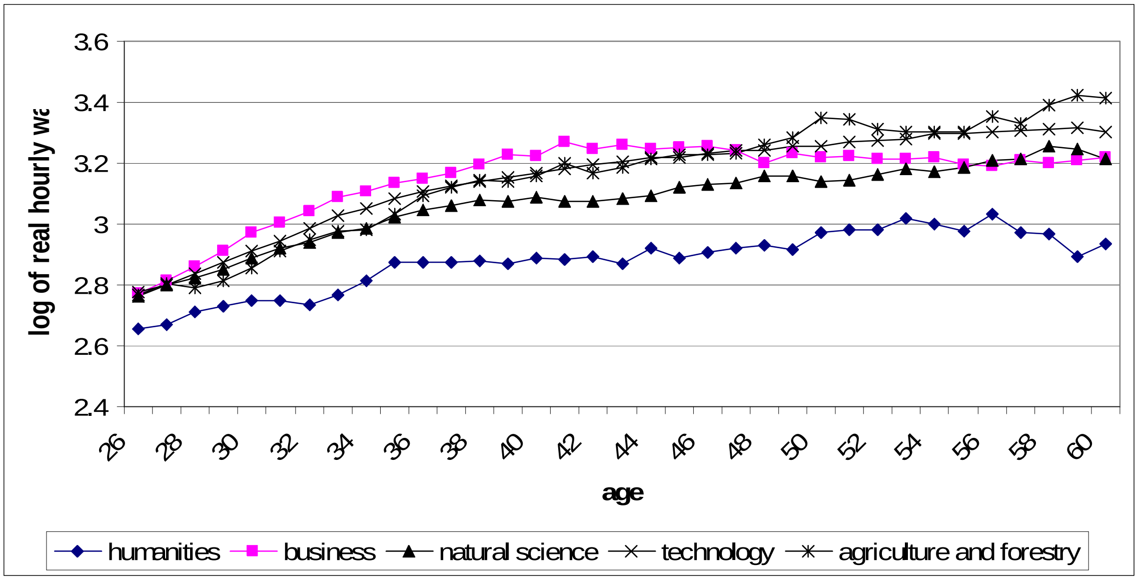


Bachelor level: women

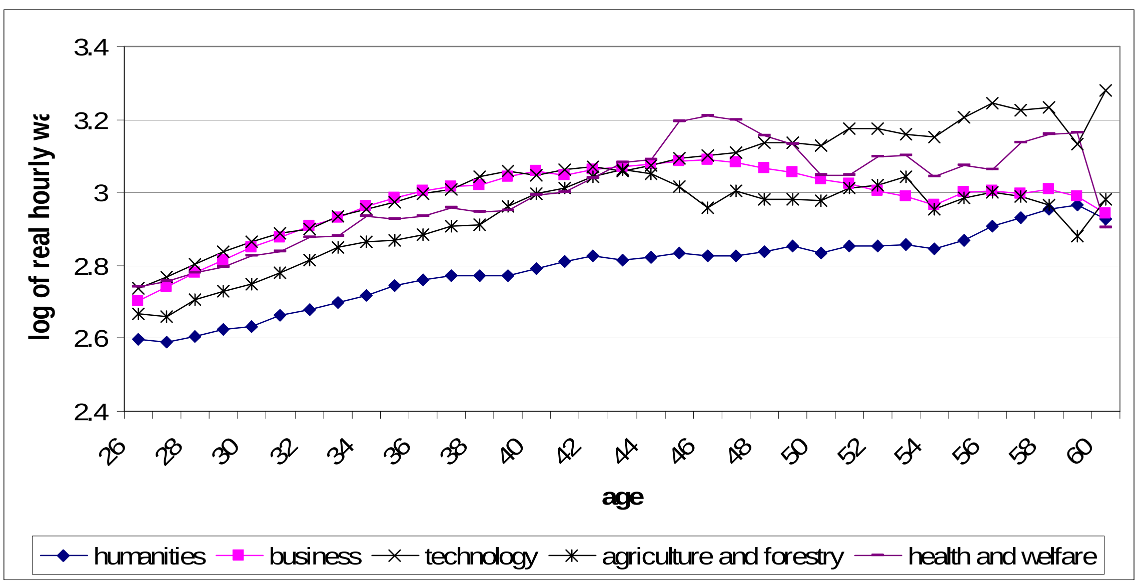


(Figure 3 continues)

Master level: men



Master level: women

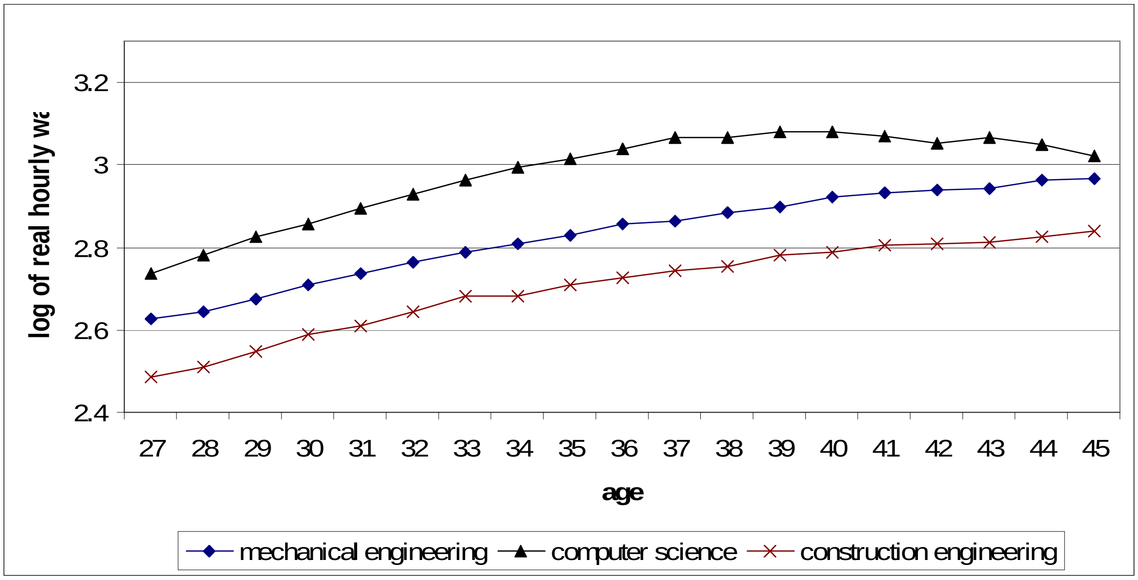


Notes:

1. Educational science and services are not included due to small number of observations. For the same reason, health and welfare are excluded from males' profiles and natural science from females' profiles.

Figure 4: Wage differences between majors within technology

Bachelor level:



Master level:

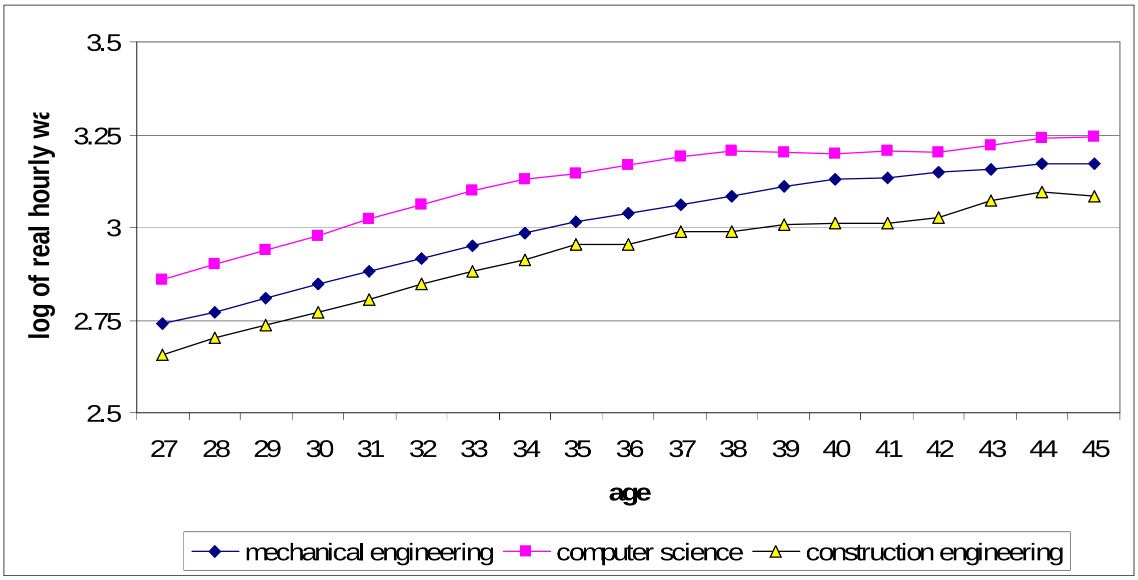


Table 1: Duncan & Duncan dissimilarity index for university majors by fields of education

Field of education	Bachelor level	Master level
Education science	0.620	0.594
Humanities and arts	0.349	0.409
Social science and business	0.350	0.130
Natural science	0.161	0.295
Technology	0.339	0.345
Agriculture and forestry	0.492	0.421
Health and welfare	0.216	0.584
Service	0.616	0.907

Table 2: Decomposition of the gender wage gap among new entrants to labor market using a less detailed measure of education

	(1) Bachelor level	(2) Master level
Gender gap in log hourly wages	0.140	0.103
Specification I		
% of the wage gap due to gender differences in education	22.8	16.4
% of the wage gap due to gender differences in other characteristics	14.4	11.1
Specification II		
% of the wage gap due to gender differences in education	25.7	15.1
% of the wage gap due to gender differences in other characteristics	14.2	16.9
Specification III		
% of the wage gap due to gender differences in education	10.9	12.8
% of the wage gap due to gender differences in other characteristics	46.9	31.7

Notes:

1. Specification I includes age, age^2, year and region dummies, gender dummy and education dummies. Specification II adds industry and firm size dummies to Specification I, and finally, Specification III adds occupation dummies to the wage model.
2. Five region, six industry and seven firm size dummies are used in the estimations. Measure of education contains eight categories. Furthermore, there are 102 and 93 different occupations represented in the data for workers with a bachelor level degree and a master level degree, respectively.

Table 3: Decomposition of the gender wage gap among new entrants to labor market using a detailed measure of education

	(1) Bachelor level	(2) Master level
Gender gap in log hourly wages	0.140	0.103
Specification I		
% of the wage gap due to gender differences in education	39.0	34.8
% of the wage gap due to gender differences in other characteristics	12.9	11.6
Specification II		
% of the wage gap due to gender differences in education	36.8	30.4
% of the wage gap due to gender differences in other characteristics	13.4	15.1
Specification III		
% of the wage gap due to gender differences in education	20.3	26.9
% of the wage gap due to gender differences in other characteristics	43.9	28.7

Notes:

1. Specification I includes age, age^2, year and region dummies, gender dummy and education dummies. Specification II adds industry and firm size dummies to Specification I, and finally, Specification III adds occupation dummies to the wage model.
2. Five region, six industry, and seven firm size dummies are used in the estimations. Measure of education contains 132 and 112 categories and there are 102 and 93 different occupations represented in the data for individuals with a bachelor level degree and a master level degree, respectively.

Table 4: Decomposition of the gender wage gap using a less detailed measure of education: total data excluding entrants

	(1) Bachelor level	(2) Master level
Gender gap in log hourly wages	0.181	0.197
Specification I		
% of the wage gap due to gender differences in education	8.9	18.2
% of the wage gap due to gender differences in other characteristics	1.3	9.9
Specification II		
% of the wage gap due to gender differences in education	13.4	13.9
% of the wage gap due to gender differences in other characteristics	-3.6	13.9
Specification III		
% of the wage gap due to gender differences in education	7.2	11.9
% of the wage gap due to gender differences in other characteristics	31.8	34.2

Notes:

1. Specification I includes age, age^2, year and region dummies, gender dummy and education dummies. Specification II adds industry and firm size dummies to Specification I, and finally, Specification III adds occupation dummies to the wage model.
2. Six region and industry dummies and seven firm size dummies are used in the estimations. Measure of education contains eight categories. Furthermore, there are 135 and 123 different occupations represented in the data for workers with a bachelor level degree and a master level degree, respectively.

Table 5: Decomposition of the gender wage gap using a detailed measure of education: total data excluding entrants

	(1) Bachelor level	(2) Master level
Gender gap in log hourly wages	0.181	0.197
Specification I		
% of the wage gap due to gender differences in education	30.3	23.2
% of the wage gap due to gender differences in other characteristics	-0.3	11.8
Specification II		
% of the wage gap due to gender differences in education	31.8	20.5
% of the wage gap due to gender differences in other characteristics	-3.4	13.3
Specification III		
% of the wage gap due to gender differences in education	20.0	17.5
% of the wage gap due to gender differences in other characteristics	27.9	31.8

Notes:

1. Specification I includes age, age^2, year and region dummies, gender dummy and education dummies. Specification II adds industry and firm size dummies to Specification I, and finally, Specification III adds occupation dummies to the wage model.
2. Six region and industry dummies and seven firm size dummies are used in the estimations. Measure of education contains 241 and 174 categories and there are 135 and 123 different occupations represented in the data for individuals with a bachelor level degree and a master level degree, respectively.

Table 6: Comparison of OLS and fixed effects results: bachelor level

	OLS			Fixed effects model		
Contribution of university major to the gender wage gap evaluated at age:	25	35	45	25	35	45
Specification I						
% of the gender wage gap due to gender differences in education	39.5	47.3	50.6	44.5	49.5	47.0
Specification II						
% of the gender wage gap due to gender differences in education	39.0	47.5	52.0	44.1	49.1	47.0
Specification III						
% of the gender wage gap due to gender differences in education	23.6	28.5	30.8	46.4	51.5	49.0

Notes:

1. Specification I includes age, age^2, year and region dummies, age*education, and age^2*education. Specification II adds industry and firm size dummies to Specification I, and finally, Specification III adds occupation dummies to the wage model.
2. Six region and industry dummies and seven firm size dummies are used in the estimations. Measure of education contains 37 categories and occupation 76 categories.
3. Gender wage gap refers to the same wage gap used in Tables 4-5, it is not an age-specific gender wage gap.

Table 7: Comparison of OLS and fixed effects results: master level

	OLS			Fixed effects model		
Contribution of university major to the gender wage gap evaluated at age:	25	35	45	25	35	45
Specification I						
% of the gender wage gap due to gender differences in education	27.2	32.0	33.3	33.5	37.1	35.0
Specification II						
% of the gender wage gap due to gender differences in education	24.0	28.6	30.4	33.3	37.1	35.5
Specification III						
% of the gender wage gap due to gender differences in education	18.0	21.8	23.7	32.1	34.2	30.2

Notes:

1. Specification I includes age, age^2, year and region dummies, age*education, and age^2*education. Specification II adds industry and firm size dummies to Specification I, and finally, Specification III adds occupation dummies to the wage model.
2. Six region and industry dummies and seven firm size dummies are used in the estimations. Measure of education contains 31 categories and occupation 69 categories.
3. Gender wage gap refers to the same wage gap used in Tables 4-5, it is not an age-specific gender wage gap.

Table 8: Gender differences in coefficients to university majors

	Bachelor level	Master level
Specification I		
$\sum_S \left(\hat{\beta}_M^S - \hat{\beta}_F^S\right)\left(\overline{X}_M^S - \overline{X}_F^S\right)$	- 0.047	-0.011
Specification II		
$\sum_S \left(\hat{\beta}_M^S - \hat{\beta}_F^S\right)\left(\overline{X}_M^S - \overline{X}_F^S\right)$	-0.043	-0.013
Specification III		
$\sum_S \left(\hat{\beta}_M^S - \hat{\beta}_F^S\right)\left(\overline{X}_M^S - \overline{X}_F^S\right)$	-0.012	0.002

Notes:

1. Specification I includes age, age^2, year and region dummies, gender dummy and education dummies. Specification II adds industry and firm size dummies to Specification I, and finally, Specification III adds occupation dummies to the wage model.
2. Six region and industry dummies and seven firm size dummies are used in the estimations. Measure of education contains 183 and 138 categories and there are 137 and 124 different occupations represented in the data for individuals with a bachelor level degree and a master level degree, respectively.
3. $\hat{\beta}_M^S$ is a parameter estimate for a major category S estimated from a male-only sample, and $\hat{\beta}_F^S$ is the corresponding term for females. $\overline{X}_M^S$ and $\overline{X}_F^S$ on the other hand refer to male and female sample means.

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Table 1A: Summary statistics for selected variables

Bachelor level:

	Men			Women		
	Obs	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**
ln hourly wage	163706	2.887	0.268	41513	2.697	0.272
age	163706	39.923	9.574	41513	38.294	10.424
age^2	163706	168.548	80.011	41513	157.505	84.194
Region:						
South Finland	163706	0.500	0.500	41513	0.582	0.493
West Finland	163706	0.362	0.481	41513	0.299	0.458
East Finland	163706	0.053	0.225	41513	0.054	0.226
The province of Oulu	163706	0.071	0.256	41513	0.054	0.226
Lapland	163706	0.014	0.116	41513	0.011	0.104
The Åland Islands	163706	0.000	0.011	41513	0.000	0.000
Field of industry:						
Manufacturing	163706	0.706	0.456	41513	0.712	0.453
Construction	163706	0.075	0.263	41513	0.035	0.184
Transportation	163706	0.029	0.169	41513	0.052	0.221
Services	163706	0.145	0.352	41513	0.143	0.350
Forest industry	163706	0.031	0.173	41513	0.017	0.130
Energy industry	163706	0.014	0.116	41513	0.041	0.199
Firm size:						
No more than 50	163706	0.113	0.317	41513	0.119	0.324
51-100	163706	0.087	0.281	41513	0.100	0.299
101-200	163706	0.139	0.346	41513	0.143	0.350
201-500	163706	0.194	0.395	41513	0.181	0.385
501-1000	163706	0.124	0.330	41513	0.110	0.312
1001-2000	163706	0.065	0.373	41513	0.058	0.377
Over 2000	163706	0.277	0.448	41513	0.290	0.454
Field of education:						
Education	163706	0.001	0.032	41513	0.013	0.113
Humanities and arts	163706	0.008	0.089	41513	0.120	0.324
Social sciences and business	163706	0.053	0.225	41513	0.456	0.498
Natural science	163706	0.008	0.090	41513	0.015	0.122
Technology	163706	0.891	0.312	41513	0.332	0.471
Agriculture	163706	0.035	0.183	41513	0.021	0.145
Health and welfare	163706	0.001	0.037	41513	0.034	0.181
Service	163706	0.003	0.050	41513	0.009	0.096

(Table 1A continues)

Master level:

	Men			Women		
	Obs	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**
Ln hourly wage	109870	3.089	0.278	49957	2.907	0.269
age	109870	38.980	8.689	49957	36.931	7.932
age^2	109870	159.497	72.636	49957	142.684	63.733
Region:						
South Finland	109870	0.593	0.491	49957	0.651	0.477
West Finland	109870	0.299	0.458	49957	0.274	0.446
East Finland	109870	0.031	0.174	49957	0.025	0.157
the province of Oulu	109870	0.067	0.250	49957	0.044	0.204
Lapland	109870	0.010	0.100	49957	0.006	0.077
the Åland Islands	109870	0.000	0.005	49957	0.000	0.004
Field of industry:						
Manufacturing	109870	0.780	0.414	49957	0.742	0.438
Construction	109870	0.020	0.141	49957	0.013	0.115
Transportation	109870	0.036	0.187	49957	0.042	0.200
Services	109870	0.126	0.331	49957	0.127	0.332
Forest industry	109870	0.011	0.106	49957	0.009	0.096
Energy industry	109870	0.026	0.160	49957	0.067	0.251
Firm size:						
no more than 50	109870	0.069	0.253	49957	0.075	0.264
51-100	109870	0.078	0.268	49957	0.085	0.279
101-200	109870	0.120	0.325	49957	0.133	0.339
201-500	109870	0.179	0.383	49957	0.163	0.369
501-1000	109870	0.124	0.329	49957	0.120	0.325
1001-2000	109870	0.066	0.391	49957	0.065	0.400
Over 2000	109870	0.365	0.481	49957	0.359	0.480
Field of education:						
Education	109870	0.003	0.058	49957	0.020	0.140
Humanities and arts	109870	0.022	0.146	49957	0.148	0.355
Social sciences and business	109870	0.148	0.355	49957	0.385	0.487
Natural science	109870	0.097	0.295	49957	0.128	0.334
Technology	109870	0.698	0.459	49957	0.255	0.436
Agriculture	109870	0.024	0.152	49957	0.040	0.196
Health and welfare	109870	0.007	0.081	49957	0.024	0.153
Service	109870	0.002	0.044	49957	0.001	0.028

Notes:

1. Occupational distributions are not presented in table 1A. Distributions of workers over educational categories are also shown only for the broad subject areas.

Table 2A: Number of subjects of degree and observations by the field of education

Number of different subjects:

Field of education	Bachelor level	Master level
Education science	22	12
Humanities and arts	56	57
Social science and business	59	47
Natural science	13	16
Technology	53	21
Agriculture and forestry	12	10
Health and welfare	16	8
Service	14	3
Unknown	2	2
Total	247	176

Number of male observations by education group:

Field of education	Bachelor level	Master level
Education science	167	373
Humanities and arts	1 311	2 394
Social science and business	8 730	16 288
Natural science	1 330	10 619
Technology	145 822	76 635
Agriculture and forestry	5 691	2 605
Health and welfare	230	731
Service	415	216
Unknown	10	9
Total	163 706	109 870

Number of female observations by education group:

Field of education	Bachelor level	Master level
Education science	536	1 004
Humanities and arts	4 962	7 376
Social science and business	18 920	19 234
Natural science	626	6 371
Technology	13 770	12 717
Agriculture and forestry	888	1 997
Health and welfare	1 405	1 195
Service	388	38
Unknown	18	25
Total	41 513	49 957